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Diversity Based Sampling for Applications in Computer Vision

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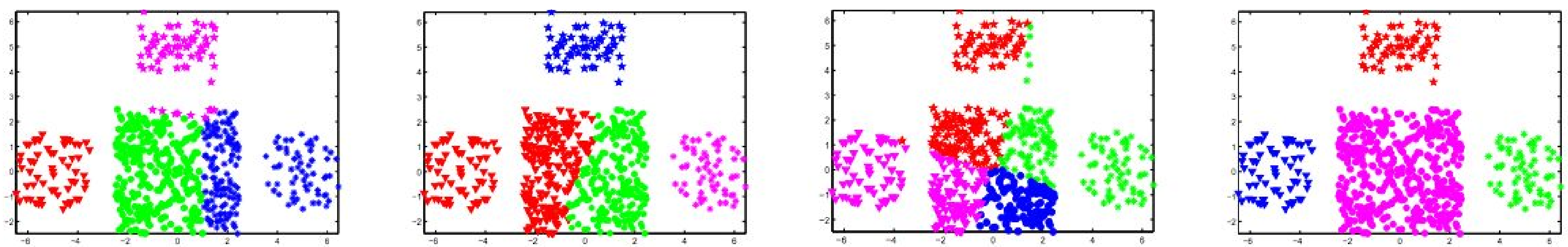
Work primarily done at Arizona State University with Pavan Turaga. Extensions of this work are being performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344

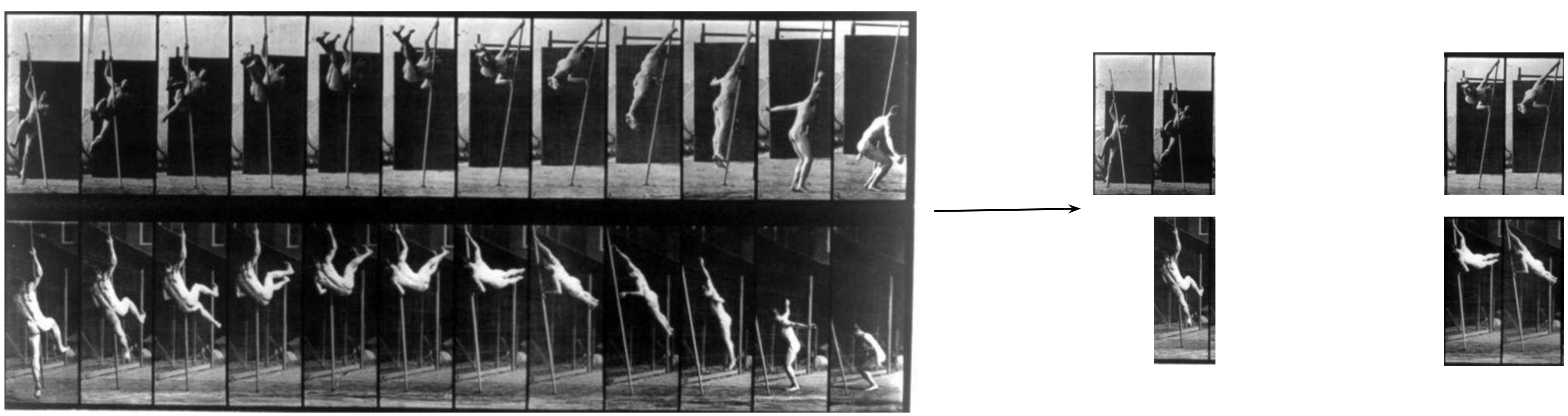
Diversity Sampling

Sampling in this context is mainly *sub-sampling,* i.e. - “Given a large dataset, what are the K most **representative** samples?”

Which paritioning gives the **right** set of “exemplars”?



Video Summarization - What is the correct summary?



Shroff, Nitesh, Pavan Turaga, and Rama Chellappa. "Video précis: Highlighting diverse aspects of videos." *IEEE Transactions on Multimedia* 12.8 (2010): 853-868.

Diversity Sampling Posed as Clustering

- Notions of Coverage and Diversity
  - Coverage (function of samples, dataset) = L-2 “quantization” error
  - Diversity(function of samples) = approximately equivalent to spread of data

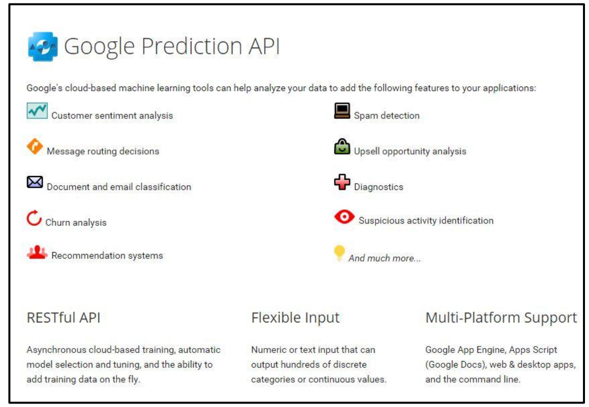
- A generic sampling algorithm must weigh these two costs according to the desired application. High diversity can make it sensitive to outliers, High Coverage can make it miss small clusters that maybe be crucial.

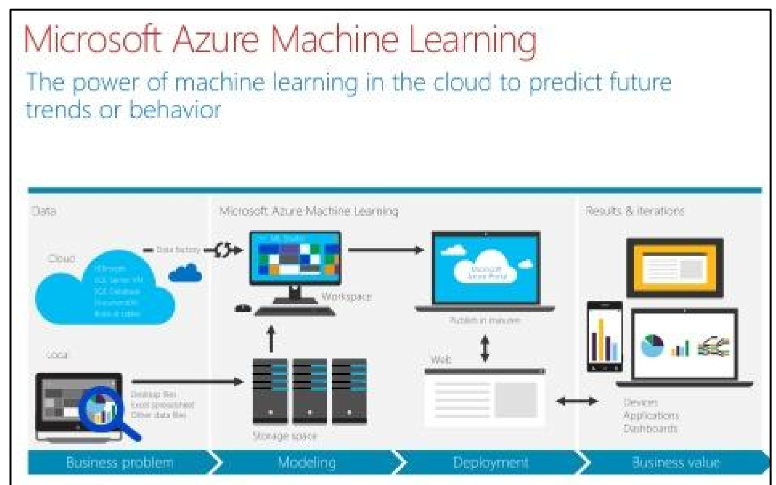
- When Diversity = 0, this reduces to the standard K-means clustering cost.

$$rep(S,X) = tr\left[\sum_{i}\sum_{F_k \in V_i}(F_k - F_i)(F_k - F_i)^T\right],$$

$$div(S,X) = tr\left[\sigma_i(F_i - \overline{F})(F_i - \overline{F})^T\right],$$

Application: Computer Vision as a service





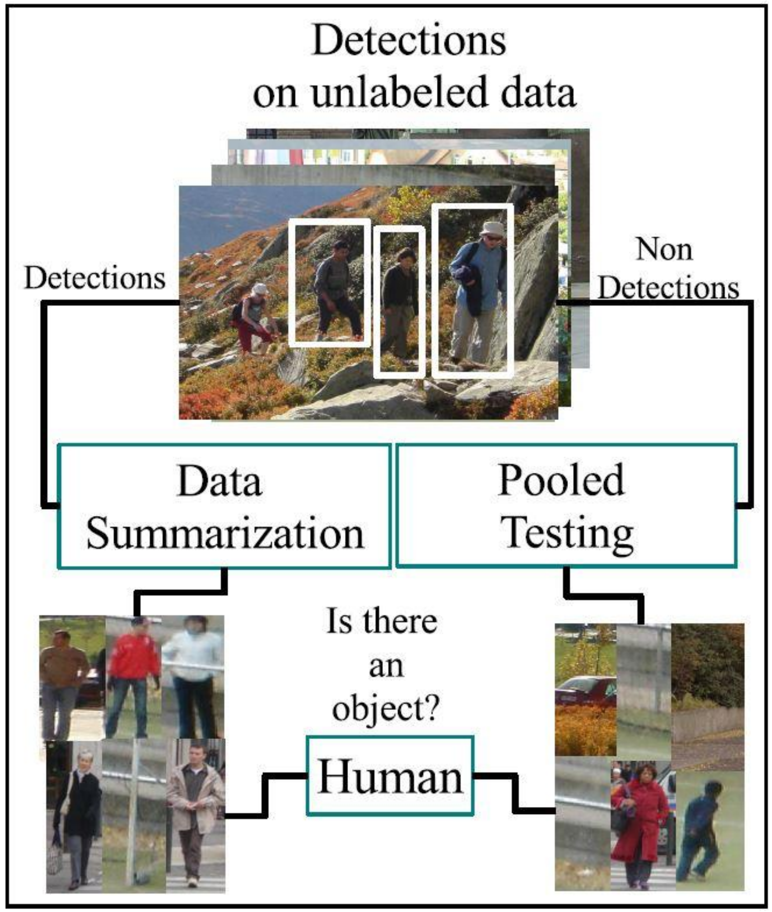
Use case: Purchasing a 3rd party classifier

Collect, annotate their application specific data and evaluate the detector.
expensive + time consuming

Use Precision-Recall curves provided for standard datasets.
dataset bias + generalizability not clear

Study the algorithm and its limitations to understand if it’s suitable for their application
time consuming + expertise may not be available + algorithm may not be public

Estimating Performance of a new classifier/detector - A “human in the loop” approach



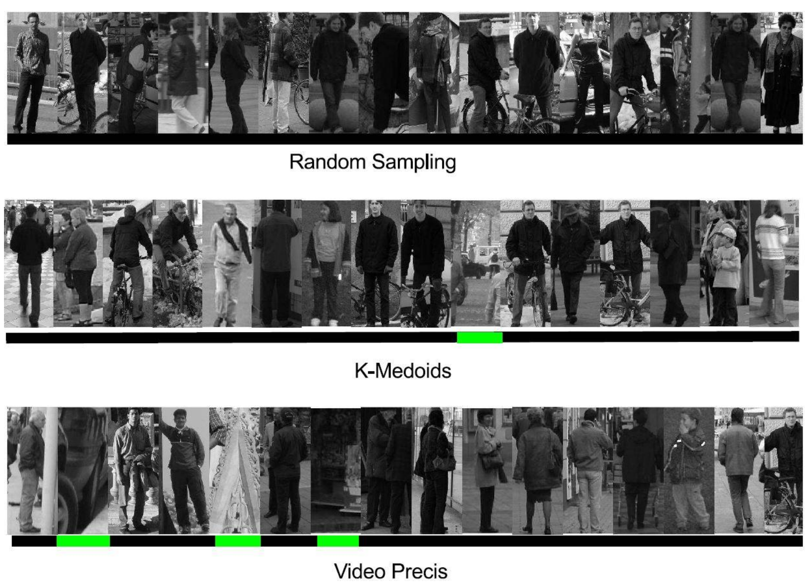
Interactively Test Driving an Object Detector: Estimating Performance on Unlabeled Data, R. Anirudh, P. Turaga, IEEE Winter Conference on Applications of Computer Vision (WACV), Mar 2014.

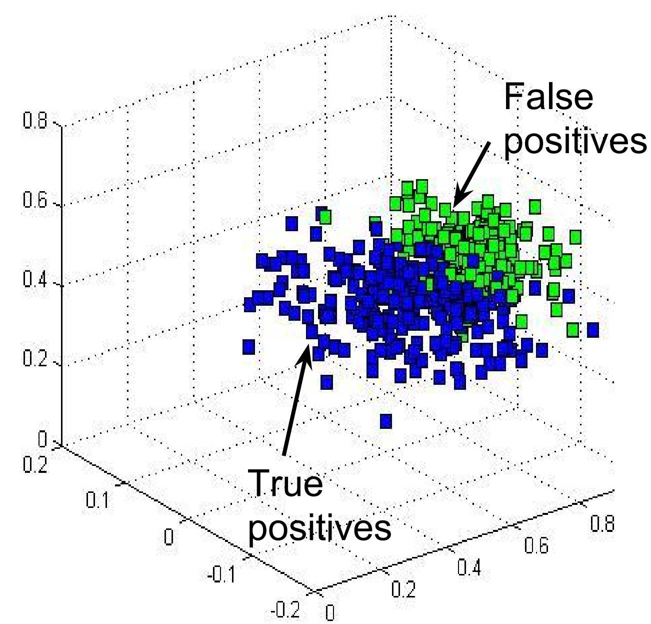
Estimating Precision

$$\text{Precision} = \frac{tp}{tp + fp}$$

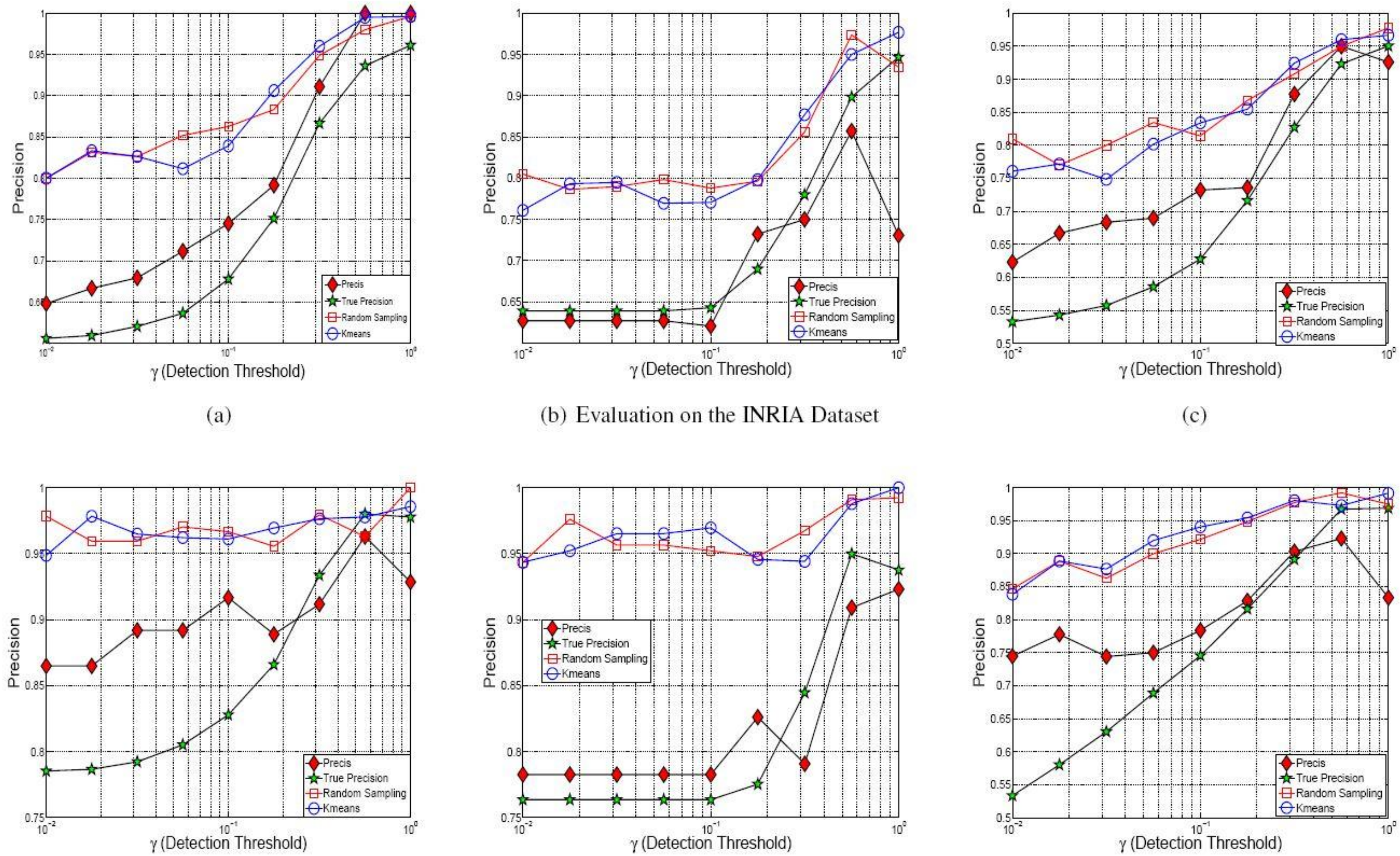
- We pose this as problem of **estimating proportions of groups** using diverse sampling.

- Summarizing techniques are able to preserve label proportions within large data sets.





Results: Precision Estimate vs True Precision obtained with Ground Truth for Pedestrian Detection



(a)

(b) Evaluation on the INRIA Dataset

(c)

Interactively Test Driving an Object Detector: Estimating Performance on Unlabeled Data, R. Anirudh, P. Turaga, IEEE Winter Conference on Applications of Computer Vision (WACV), Mar 2014.

Online diverse sampling

Online K-means:

- Initialize k-centers
- Conduct a competition between k centers to see which center “wins”

$$m = \operatorname*{argmin}_k \; d(x_i, \mu_k)$$

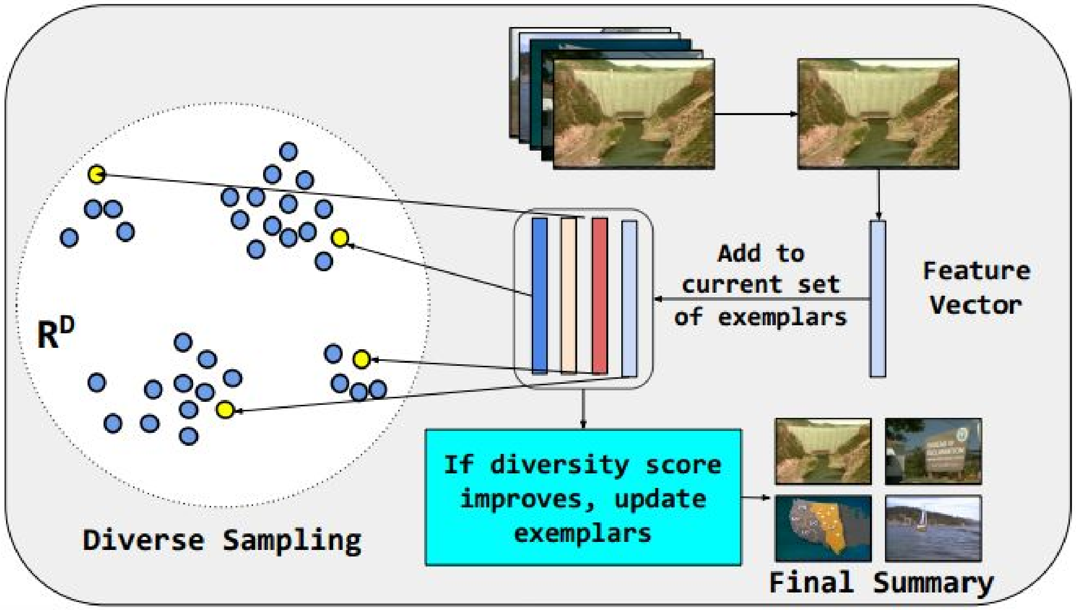
- Assign that data point to the center

$$\mu_m^{(t+1)} = \mu_m^t + \alpha(x_i - \mu_m^t)$$

Online diverse sampling - modifies the winning criterion to take diversity into account

$$d(k) = \beta \, ||x_i - \mu_k||^2 + C(1-\beta)\,\texttt{divscore}(\boldsymbol{\mu}_{k\leftarrow i}) - \zeta,$$

Maximizing diversity of chosen frames



Update if winning criterion is satisfied

$$\mu_m^{(t+1)} = \mu_m^t + \alpha(x_i - \mu_m^t)$$

Diversity measure : Volume of approximate convex polytope

Anirudh, Rushil, Ahnaf Masroor, and Pavan Turaga. "Diversity promoting online sampling for streaming video summarization." *Image Processing (ICIP), 2016 IEEE International Conference on*. IEEE, 2016.

Results: Online Video Summarization Performance Comparing with Human Generated Summaries

Sampling Algorithm	U1	U2	U3	U4	U5	Online?
K-medoids	0.191	0.199	0.179	0.199	0.193	✗
Random	0.173	0.165	0.176	0.186	0.179	✗
Uniform	0.190	0.196	0.188	0.200	0.193	✗
Precis [3]	0.227	0.219	0.225	0.240	**0.245**	✗
Online K-medoids	0.141	0.129	0.131	0.146	0.143	✓
Proposed	**0.240**	**0.224**	**0.234**	**0.253**	0.232	✓

Conclusion

- Sub sampling is an important aspect of machine learning and computer vision. Effective sampling strategies can give interesting insights into large datasets

- Diversity based sampling generalizes traditional clustering in a way that can benefit a variety of applications.

- Future work includes designing better measures of diversity -- made challenging due to its subjective nature.